Grape clusters and foliage detection algorithms for autonomous selective vineyard sprayer

Ron Berenstein[1]

Ohad Ben Shahar[2], Amir Shapiro[3], Yael Edan[1]

[1]Department of Industrial Engineering & Management

[2]Department of Computer Science

[3]Department of Mechanical Engineering

Ben-Gurion University of the Negev, Israel

E-mail of corresponding author: berensti@bgu.ac.il

Abstract

While much of modern agriculture is based on mass mechanized production, advances in sensing and manipulation technologies may facilitate precision autonomous operations that could improve crop yield and quality while saving energy, reducing manpower, and being environmentally friendly. In this paper we focus on autonomous spraying in vineyards and present four computer vision algorithms that facilitate selective spraying. In the first set of algorithms we show how statistical measures, learning, and shape matching can be used to detect and localize the grape clusters to guide selected application of hormones to the fruit but not the foliage. We also present another algorithm for the detection and localization of foliage in order to facilitate precision application of pesticide**.** All image processing algorithms were tested on data from movies acquired in vineyards during the growing season of 2008 and their evaluation includes analyses of the potential pesticide and hormone reduction. Results show 90% percent accuracy of grape cluster detection leading to 30% reduction in the use of pesticides. The database of images is placed on the internet and available to the public for other to continue develop detection algorithms'.

Keywords: precision agriculture, image processing, edge detection, decision tree, machine learning

Introduction

Targeted spraying is one of the immediate and accessible domains of precision agriculture whose benefits in reducing pesticide application supports not only reduced direct costs in materials but also environmental concern [1, 2] and reduced medical hazards [3, 4]. In present day vineyards, for example, spraying is done homogeneously along the rows, without considering areas with low foliage density or gaps between trees. Estimates indicate that 10%–30% of the pesticide agent can be reduced by using smart sprayers targeted towards foliage only [5].

This paper is part of a larger project aiming to design, build, and test an autonomous, site-specific spraying robot for vineyards (Figure 1). Here we focus on image processing aspects that lie at the heart of this autonomous selective sprayer. This work deals with two types of pesticide spraying techniques: spraying the foliage and spraying the grape clusters. Evaluation of the image processing algorithms includes analysis of the potential pesticide reduction. Currently, foliage spraying is done using a spraying boom that covers its entire height. The spraying boom is dragged along the row and sprays the entire foliage without considering gaps between trees or the varying density of foliage.

(a) (b)

Figure 1 - Vineyard spraying robot.

While foliage spraying is done nonselectively, spraying the grape clusters is done in one of two ways. Often, a human carries a portable sprayer and sprays the grape clusters individually. This operation is very time consuming and labor intensive. Alternatively, grape clusters can be sprayed nonselectively by adjusting a sprayer boom to the height of the grapes, usually from 50 cm to 100 cm above ground. Then, the spraying boom is dragged along the row and sprays the entire grape clusters strip. This type of spraying technique harms the leaves that are being sprayed; it wastes a lot of spraying agent, and pollutes the environment.

Reducing the use of pesticide is one of the incentives for selective spraying. Here we argue that such savings can be achieved in both the foliage spraying process and in the grape cluster spraying. In particular, we wish to detect gaps between trees in order to reduce pesticide use during foliage spraying, and detect grape clusters for targeted spraying. A spraying robot equipped with these detection capabilities and a pan/tilt head with a spray nozzle would be able to spray selectively and precisely, saving significant amounts of spraying material. As mentioned, here we focus on developing image processing algorithms for foliage and grape cluster detection. While other evaluation criteria are also possible, here we analyze the performance of these algorithms based on material reduction criteria.

Several autonomous robotic sprayers have been developed. An autonomous tractor for spraying was developed at the Robotics Institute of Carnegie Mellon University [6]. Kevin et al. [7] developed a fluid handling system to allow on-demand chemical injection for a machine-vision controlled sprayer. The system was able to provide a wide range of flow rates of chemical solution. Balsari et al. [8] conducted a three-year experimental study in apple orchards in southern Piedmont to determine the quality of spray deposition on the canopy, the incidence of ground losses, and drift effect according to the sprayer adjustment. Results indicated that the application of reduced volumes (300–500 l/ha) calibrated according to the plants' growth stage, enabled better coverage of the target and reduced ground losses, although increasing drift risks were registered when fine droplets were sprayed.

Manor et al. [9] used turbulent air-jet nozzles, which helped to penetrate even dense canopies and accurately deposit the droplets on the different leaves on both leaves sides. By using several turbulent air-jet nozzles, vineyard sprayer accuracy was adjusted.

Wiedemann et al. [10] developed a spray boom that would sense mesquite plants. Sprayers were designed for tractors and all-terrain vehicles. Controllers were designed to send fixed duration pulses of voltage to solenoid valves for spray release through flat-fan nozzles when mesquite canopies interrupted the light. The levels of mesquite mortality achieved were equivalent to those levels that have been achieved by ground crews hand spraying the same chemical solution.

A machine vision sensing system and selective herbicide control system was developed and installed on a sprayer by Steward et al. (2002). The system operated with an overall accuracy of 91%. Significant differences in pattern length variance and mean pattern width were achieved across speed levels ranging from 3.2 to 14 km/h. Spray patterns tended to shift relative to the faster travel speeds. A precision sprayer was developed and tested with a robust crop position detection system (Nishiwaki et al. 2004) for varying field light conditions for rice crop fields. Zheng [11] developed a tree image processing, tree crown recognition, and smart spray execution system. The tree imaging system included a CCD camera, an image grabber, a computer, and experimental set up. The tree crown recognition system based on BP neural networks was developed as the spraying of pesticides depended greatly on the tree crown type. Six typical tree crowns (cone,

spherical, cylindrical, umbellate, etc.) could be determined. The spray execution system consisted of a spraying table, nozzles, solenoid valves, and relays. Similarly, autonomous operation of a speed-sprayer in an orchard was achieved using fuzzy logic control of image processing and ultrasonic sensors, and steered by two hydraulic cylinders (Shin et al. 2002). Ogawa et al. (2006) developed a spraying robot for vine production and demonstrated that the robot is able to spray more uniformly than a human operator and to reduce the amount of spraying agent; no quantitative results were reported.

Table 1 - Recent work on robotic sprayers.

Application	Sensor	Results	Reference
Rice	NIR	Reduced pesticide use (no quantitative results)	[12]
Clean road shoulder	Color CCD	Reduced pesticide use by up to 97%	[13]
Weed sprayer	Color video	Reduced up to 91% with max speed of 14 [km/h]	[14]
Orchards	Color + Ultrasonic	Not Reported	[15]
Weed in cotton	Color CCD	Sprayed 88.8% of weed while correctly rejecting and not spraying 78.7% of cotton	[16]
Grapes	ultrasonic	Not Reported	[17]
Tomatoes	RGB camera	8% incorrect spray (4 of 51)	[18]
Palms	Stereo camera	Scale-down model proved the ability to track palm trees	[19]
Greenhouses	CCD Camera	Presented the ability to navigate in artificial greenhouse	[20]
Weed control	USB camera	83% success rate with less than 3 seconds for target	[21]

Image Processing Algorithms

In this paper we present two types of image processing algorithms: a Foliage Detection Algorithm (FDA) and a Grape clusters Detection Algorithms (GDA). The FDA is based on the fact that the foliage color is green. Two filters operate on the captured image; one removes white pixels (sky, sun, etc.) and the other traces the green pixels. These filters are combined to produce the foliage image (Figure 2). The FDA algorithm is not designed to separate the foliage of the close tree from the foliage of a tree in the next row. Such a separation is not necessary in order to identify the tree foliage and the grapes clusters.

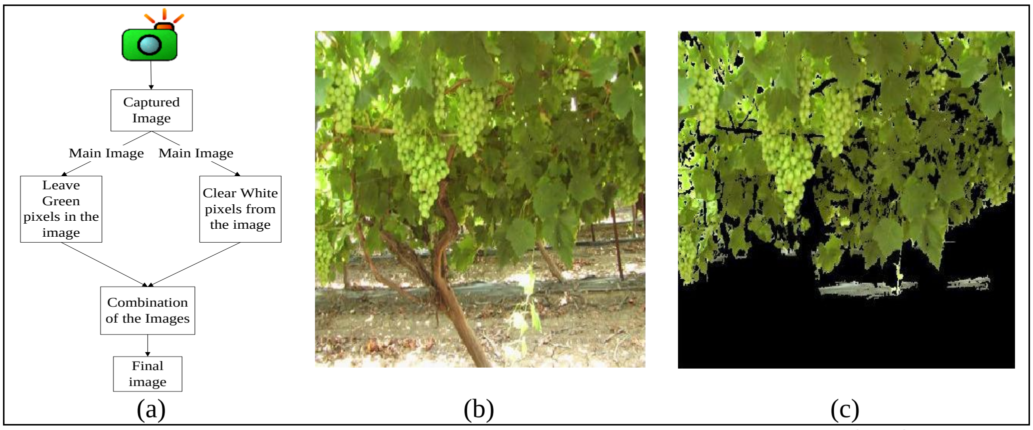

Figure 2 - Foliage Detection Algorithm, (a) algorithm block diagram, (b) captured image, (c) final foliage image.

Three GDAs were developed. The first GDA (Algorithm 1) is based on the difference in edge distribution between the grape clusters and the foliage. The algorithm was created by examining images from the vineyard and noticing that regions of grape clusters contain more edges than those in foliage regions. The first GDA includes three main stages (Figure 5): FDA, edge detection, and thresholding the high edge from the low edge areas. The edge detection algorithm was based on the Canny Edge Detection Algorithm [22]. The Canny algorithm was empirically selected after experimenting with different edge detection algorithms on an assortment of 100 grape images. Examples of different edge detection methods are shown in Figure 3. These edge detection methods operated (Figure 3b) after

converting the image to a gray-scale image. By observing the binary results in Figure 3 - Different edge detection methods. (a) Sobol, (b) Prewitt, (c) Roberts, (d) Laplacian of Gaussian, (e) Zero-cross, (f) Canny.
Figure 3 one can see that Figure 3 - Different edge detection methods. (a) Sobol, (b) Prewitt, (c) Roberts, (d) Laplacian of Gaussian, (e) Zero-cross, (f) Canny.

f (Canny method) is the most detailed. Quantitative analyses of the number of edges in the image are presented in Figure 4 for average results of 100 vineyard edge images.

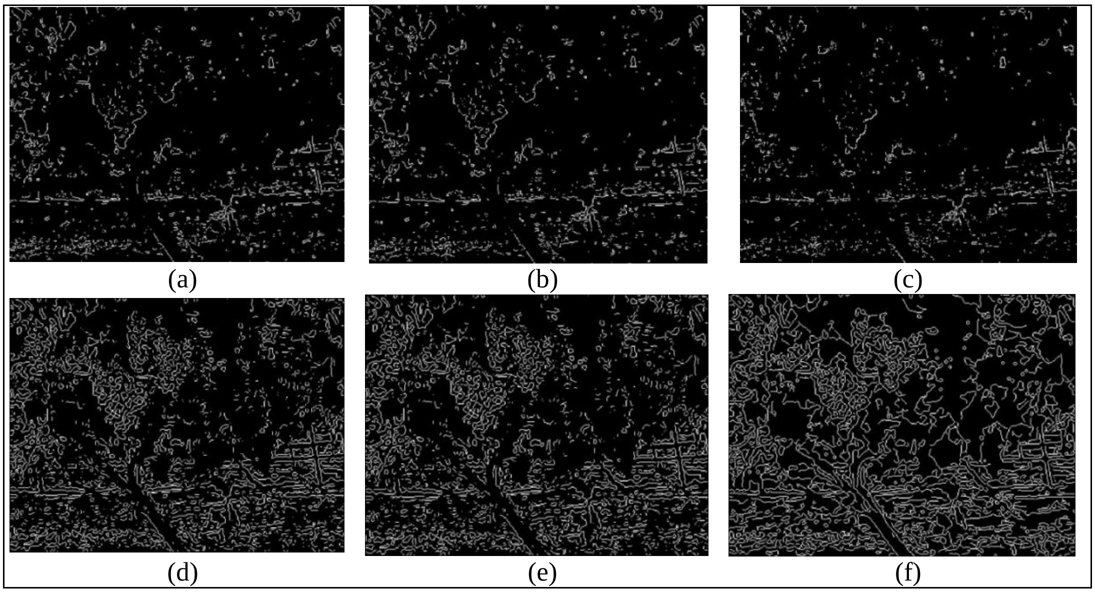

Figure 3 - Different edge detection methods. (a) Sobol, (b) Prewitt, (c) Roberts, (d) Laplacian of Gaussian, (e) Zero-cross, (f) Canny.

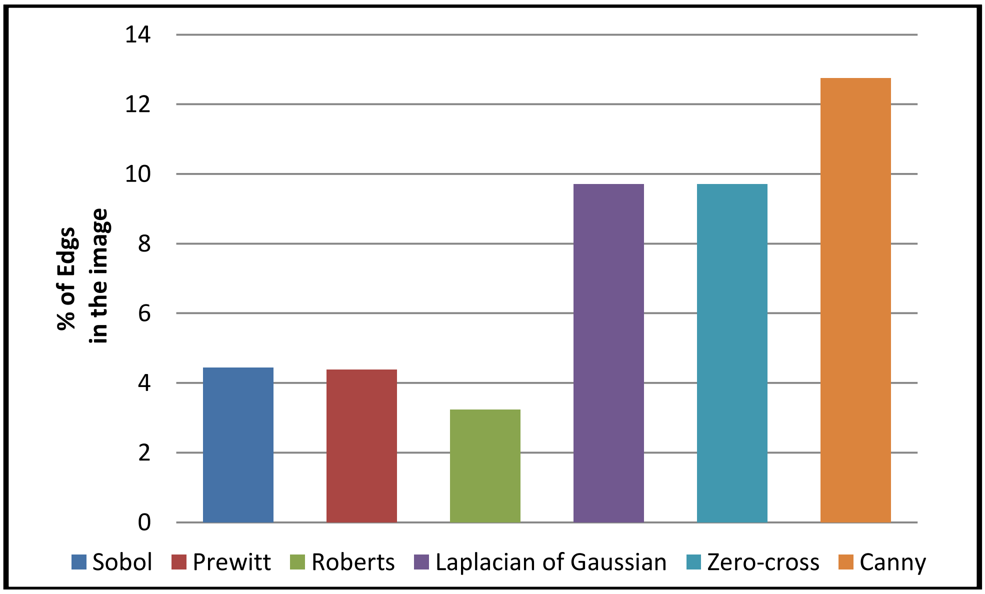

Figure 4 - Quantitative analyses of edges in images.

Results indicated that the Canny algorithm produced the most highly detailed edge images (Figure 4); hence, it was selected for this assignment. These results correspond to previous research [23, 24].

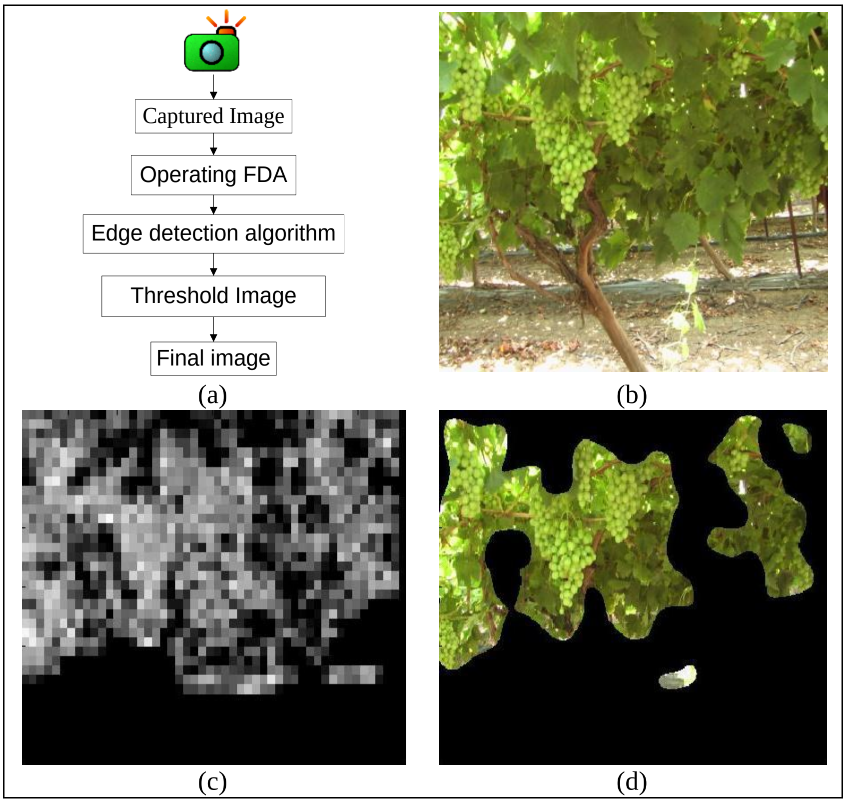

Figure 5 - Grape Detection Algorithm. (a) algorithm block diagram, (b) captured image, (c) edges image, (d) final grape image.

Algorithm 1 – Edged based algorithm

Input: Capture Image

Output: Gray_Image that contains only grape clusters

```
For all pixels in main image
    If Red channel > 190 & Green channel > 190 & Blue channel > 190 then
        Pixel = 0
    End if
    If Green channel > Red channel & Green channel > Blue channel & Green channel > 70 then
        Leave pixel in image
    else
        Pixel=0
    End if
End for
For all image channels
    Operate Canny algorithm
End for
Gray_Image=sum of canny algorithm
Smooth Gray_Image using two-dimensional convolution
For all pixels in Gray_Image
    If pixel value<threshold
        Pixel=0
    End if
End for
Delete small area objects from Gray_Image
Return Gray_Image
```

The second GDA is based on a decision tree algorithm. First, the color image is represented in both the common RGB representation and the perceptually motivated HSV (hue, saturation, and intensity) representation. Then, supervised patches taken from the grape areas and the foliage areas are used to extract the following parameters from each of the R, G, B, H, S, and V channels: mean

value, standard deviation, and the mean and standard deviation of the gradient magnitude. Using three patch sizes, 72 different parameters were extracted from each image (Table 2) and a total of 1708 samples of these parameters were extracted from the entire image collection. Pearson’s Correlation [25] was used to filter the parameters that have weak correlation to the classified data: high Pearson correlation represents high correlation between the parameter and the classification. All parameters with Pearson correlation less than 0.5 were filtered out. The dataset was divided into two groups of 70% and 30% for training and validating, respectively. We used the C5.0 algorithm [25] for training the decision tree.

Table 2 - Decision tree parameters.

mask diameter = 11							
mean				standard deviation			
Image		Gradient Image		Image		Gradient Image	
R,G,B	H,S,V	R,G,B	H,S,V	R,G,B	H,S,V	R,G,B	H,S,V
mask diameter = 15							
mean				standard deviation			
Image		Gradient Image		Image		Gradient Image	
R,G,B	H,S,V	R,G,B	H,S,V	R,G,B	H,S,V	R,G,B	H,S,V
mask diameter = 21							
mean				standard deviation			
Image		Gradient Image		Image		Gradient Image	
R,G,B	H,S,V	R,G,B	H,S,V	R,G,B	H,S,V	R,G,B	H,S,V

Once the decision tree is constructed, it can be used for classification (Algorithm 2): the same parameters that were extracted during the learning process are extracted from the given image around each pixel, and then each pixel is classified as grape or non-grape using the decision tree. Results of the second GDA is shown at Figure 6.

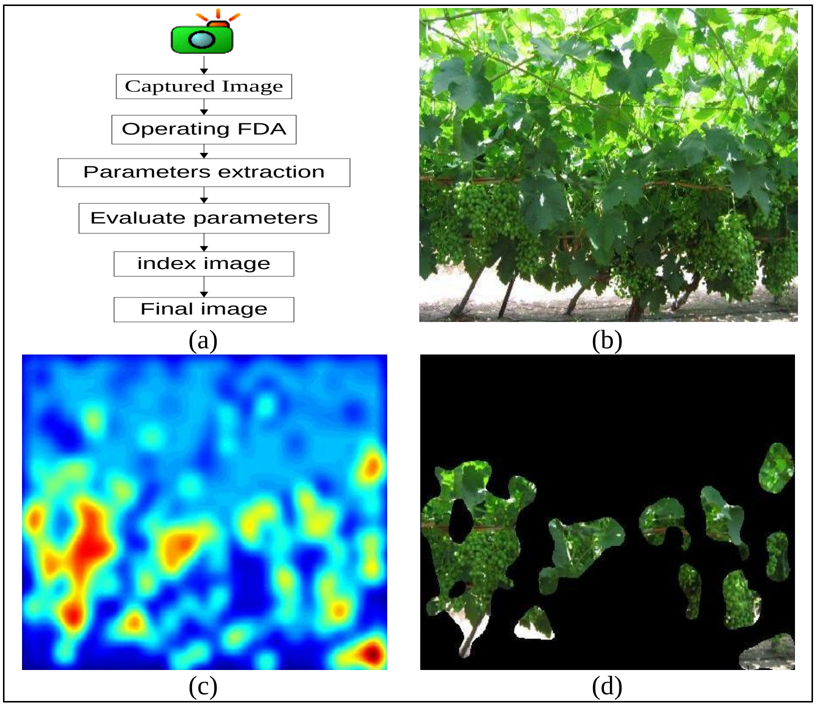

Figure 6 - Grape Detection Algorithm, (a) algorithm block diagram, (b) Captured Image, (c) Index Image, (d) Final Image.

Algorithm 2 - Decision tree algorithm

Input: Capture Image

Output: Gray_Image that contains only grape clusters

```
For all pixels in Capture image
    If Red channel > 190 & Green channel > 190 & Blue channel > 190 then
        Pixel = 0
    End if
    If Green channel > Red channel & Green channel > Blue channel & Green channel > 70 then
        Leave pixel in image
    else
        Pixel=0
    End if
End for
For all pixels in Capture image
    Locate the center of the mask at the pixel
    Extract features from the mask
    Operate decision tree classification on the features
    {
        Return Gray_Image = 0 in case of foliage, 1 in case of grapes
    }
End for
Smooth Gray_Image using two-dimensional convolution
For all pixels in Gray_Image
    If pixel value<threshold
        Pixel=0
    End if
End for
Delete small area objects from Gray_Image
Return Gray_Image
```

The third GDA (Algorithm 3) is based on pixel comparison between edge representations of the captured image with a predesigned edge mask that represents grapes. A large number of overlapping pixels between the edged image and the edge mask indicates that the area in the image is similar to the area in the mask and therefore it is a grape cluster. The algorithm uses a moving average and compares the mask over the edged image using two-dimensional convolutions. Four-edge masks were evaluated (Figure 7): (a) edge mask of single grape, (b) edge mask of grape cluster, (c) perfect circle with varied thickness and diameter of one grape, the center of the mask equals zero, (d) perfect circle with varied thickness and diameter of one grape, the center of the mask is negative.

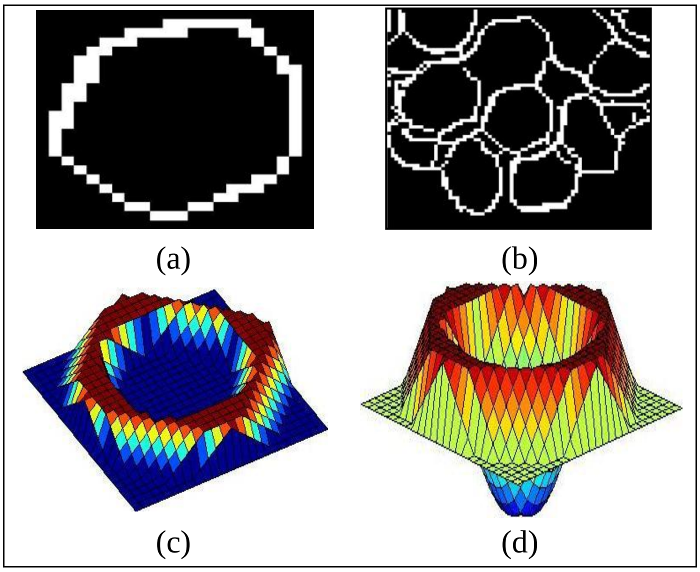

Figure 7 - Four edge Masks. (a) single grape, (b) grape cluster, (c) center zero, (d) negative center.

In order to choose the best mask for the algorithm, the masks needed to be evaluated and compared. In the evaluation process the detection algorithm was set to 90% detection of grape clusters and the percent of pesticide reduction was measured. Each mask was operated on one edged image and by applying a varying threshold on the index image (Figure 8(c)) the grape cluster detection rate was set to 90%. By comparing the detected area (Figure 8(d)) to the traditionally sprayed area, the pesticide reduction rate can be measured.

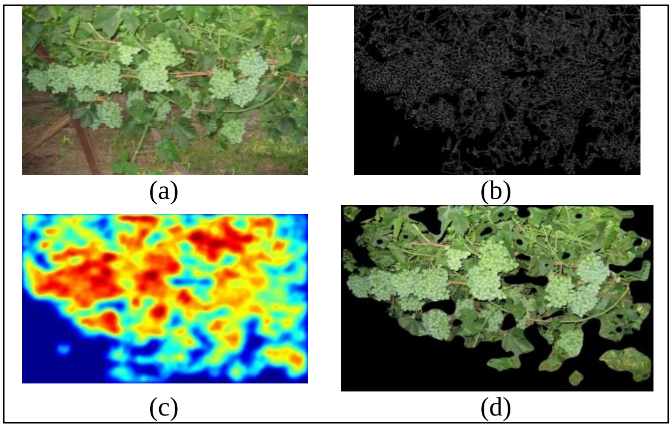

Figure 8 - Grape detection algorithm. (a) Captured image, (b) Edged image (c) Index image, (d) Final image.

Table 3 - Performance of the four masks.

Mask	Detection [%]	Pesticide reduction [%]
grape cluster	90.45	24.08
center zero	89.95	23.90
single grape	90.10	22.20
negative center	90.53	12.73

The evaluation of the different masks over a set of 100 images indicated that the mask with the largest pesticide reduction is the grape clusters mask (Figure 7 (b)). Reduction rates for the different masks with a detection rate of 90% are presented in Table 3.

Algorithm 3 - Edged mask besed algorithm

Input: Capture Image

Output: Gray_Image that contain only grape clusters

```
For all pixels in Capture image
    If Red channel > 190 & Green channel > 190 & Blue channel > 190 then
        Pixel = 0
    End if
    If Green channel > Red channel & Green channel > Blue channel & Green channel > 70 then
        Leave pixel in image
    else
        Pixel=0
    End if
For all image channels
Operate Canny algorithm
End for
Gray_Image=sum of canny algorithm
For all pixels in Gray_Image
    Locate the center of the mask at the pixel
    Gray_Image (pixel)= Sum the number of coincident pixels
End for
Smooth Gray_Image using two-dimensional convolution
For all pixels in Gray_Image
    If pixel value<threshold
        Pixel=0
    End if
End for
Delete small area objects from Gray_Image
Return Gray_Image
```

Experimental methods

The camera (IDS Inc., uEye USB video camera with a Wide VGA [752 × 480] resolution) was attached to a custom-built towing cart specially designed for the image sampling (**Error! Reference source not found.**Figure 9). The cart imitates the movement of a wheeled vehicle so as to ensure the images taken using the cart are as similar as possible to images taken from a moving wheeled robot. The camera was connected to a DELL® Core2 laptop computer. Images were acquired using Matlab® Image Acquisition Toolbox and saved for offline processing. Field experiments were conducted during the growing season of 2008. The cart was dragged through the vineyard row and images were captured and stored on the computer. We repeated this process every two weeks from mid April to the end of July 2008. The dragging speed of the cart was set at 4 to 5 [km/h], to imitate the speed of manual spraying.

Figure 9 - Experimental towing cart.

To obtain a large variety of grape and foliage images, the experiments were performed in two different vineyards, one with green grapes and the other with red grapes. 100 random images were extracted from 16 different movies that were sampled in the field. For comparison and algorithm test accuracy, the grape cluster areas were marked manually in each image. The whole dataset of raw images is available for others to use on: http://hl2.bgu.ac.il/users/www/8141/vineyard images

Imaging evaluation methodology

The machine vision algorithms were evaluated by comparing the results of the Grape Detection Algorithms (GDA) to ground truth data marked manually by expert human observers. Two parameters were evaluated: the detection percentage of the marked area and the percentage of pesticide agent reduction as a result of using these machine vision algorithms compared to spraying the whole area.

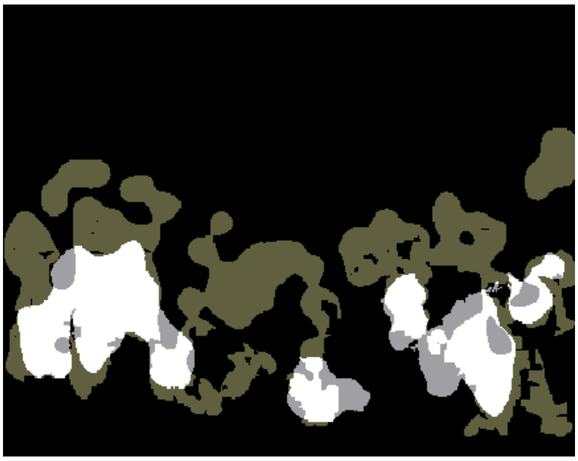

Figure 10 - Comparison between marked and machine vision detection.

The evaluation of the detection percentage is demonstrated in Figure 10. The figure is divided into four different shades – white, bright gray, dark gray, and black, which represent the true grape areas that the algorithm found (True-True TT), the true grape areas that the algorithm did not find (False-True FT), the areas that the algorithm marked as grape but was foliage (True-False TF), and the foliage area that the algorithm marked as foliage (False-False FF), respectively. The percentage of TT was the main parameter for the algorithm evaluation because of its important effect on the quality of the grape spraying. The percent reduction of spraying material was evaluated by comparing the current spraying method in which the farmer sprays a strip of 50 [cm] that contains most of the grape clusters (represented in Figure 10 as the dark gray and white areas). Comparison between this strip and the white area in Figure 11 yields the percentage of saved pesticide.

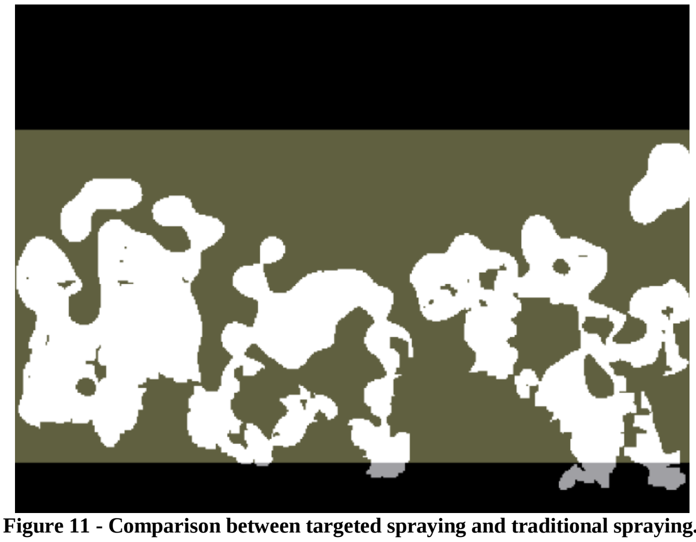

Figure 11 - Comparison between targeted spraying and traditional spraying.

The detection evaluation parameters (TT TF FT FF) were optimized by changing the relevant variables in the algorithm and resetting the range of each of these variables. An example of this optimization is shown in Figure 12 and Figure 13 for optimizing the threshold value of the edged mask algorithm and the moving mask algorithm respectively. Using these graphs it is possible to select the proper threshold according to the agricultural demand of grape detection.

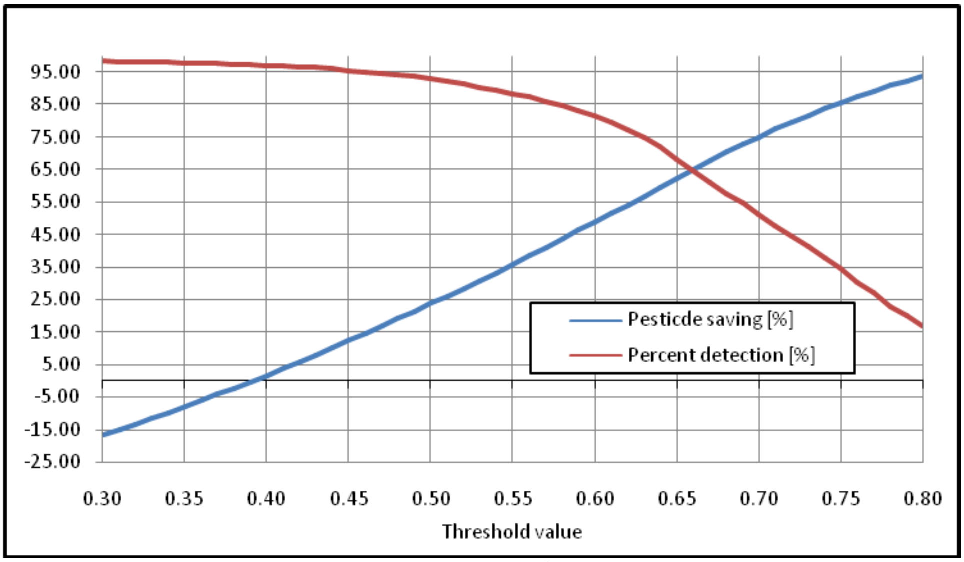

Figure 12 - Optimizing threshold value for edge-based algorithm.

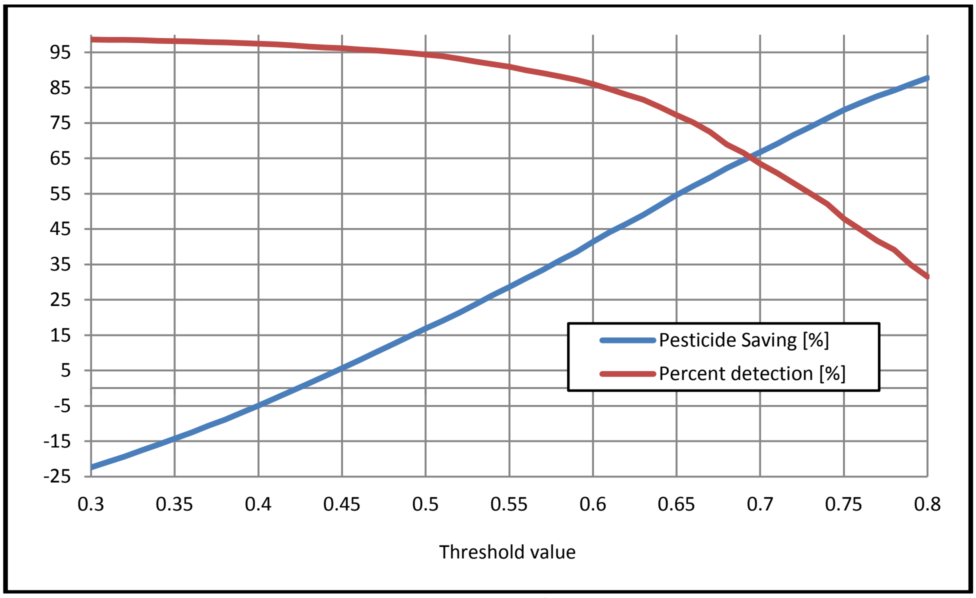

Figure 13 - Optimizing threshold value for moving mask algorithm.

Every possible combination of the different variables in the range was tested on the dataset of 100 representative images. For each combination, the mean of the detection quality and the mean of the reduction of pesticides were calculated. The optimization of one variable (threshold value) is shown in Figure 14 - Relation between detection rate and pesticides saving. (a) Edge based, (b) Decision tree.

Figure 14, where each point represents a different threshold value and the resulting detection quality and pesticide reduction. For example, if the farmer requires 80% grape detection, using the different curves (Figure 14), it is possible to find which parameters to use and the pesticide reduction rate for this detection rate.

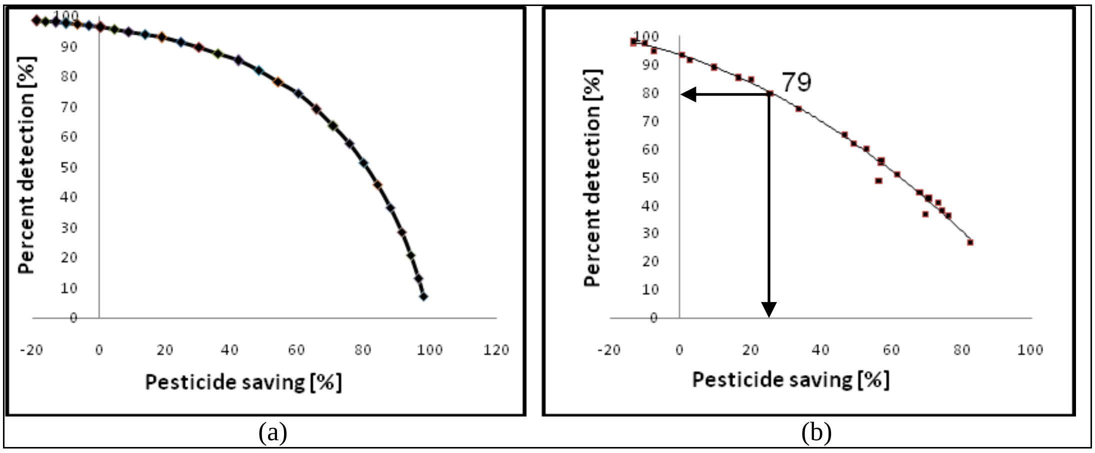

Figure 14 - Relation between detection rate and pesticides saving. (a) Edge based, (b) Decision tree.

Results

Before describing the detection results let us discuss the spraying speed in relation to the algorithm processing time. In order for the application to work in real-time conditions, the following condition must be met: $v \cdot t \leq x$,where v is the robot's speed, t is the machine vision processing time, and x is the real world field of view length. Lab measurements showed that the real world length as perceived by the camera is 2 m, with 1.5 m distance from the camera to the grape clusters. The robot speed as it relates to the processing time can be calculated by using $v \leq x/t$ and substituting x =2 m. The maximal robot speed as a function of the processing time is shown in Table 4.

Table 4 - Robot speed in realation to processing time.

Algorithm	Processing time [S]	Maximal Robot speed [m/s] (km/h)
Edge Based	0.65	3.07 (11.07)
Decision Tree	1.43	1.39 (5.03)
Moving Mask	1.15	1.73 (6.26)

Savings potential is the percent of maximal feasible saving possible in a given image. The Saving Potential depends on the percent of grape clusters in the given image. Saving Percent of 100 means that there are no grapes in the image and there is no need to spray. The Saving Potential is in inverse proportion to the percent of grape clusters in the image. The relation between the percent of grape clusters in real field images to the Saving Potential is shown in Figure 15. The Saving Potential is increased as a result of the small number of grape clusters in the image. Low numbers of grape clusters could be a result of images taken early in the season or a gap between the vineyard trees.

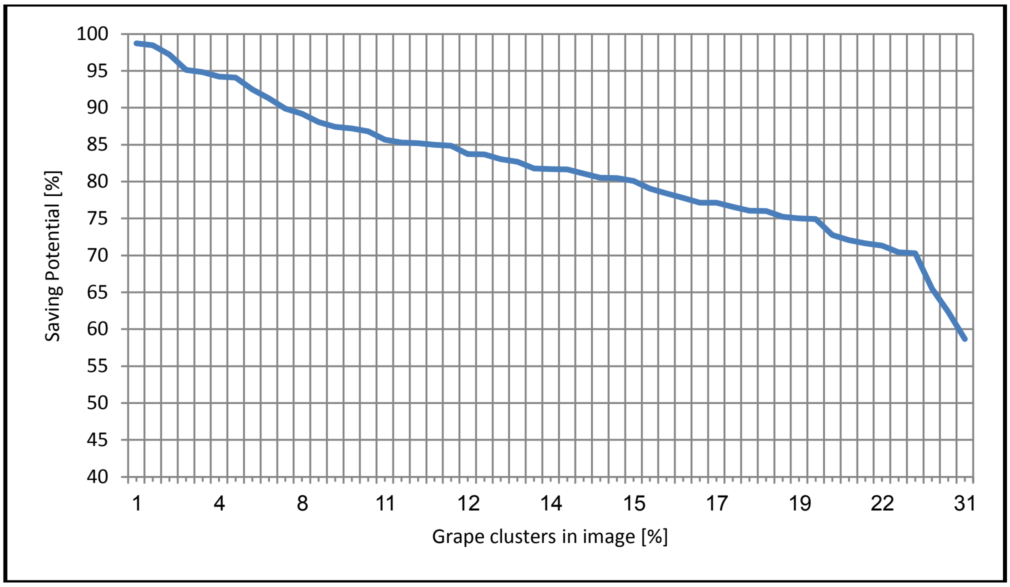

Figure 15 - Relation between saving potential and grape clusters in the image.

In the following table the detection results using the three GDAs are summarized (Table 5). One can see that between 25% and 30% of the pesticide agent is saved. The detection of grapes as grapes is more than 90%, which is considered very high with respect to other agriculture detection systems. The overall detection results show high ability to detect grape clusters in the vineyard environment.

Table 5 - Final detection results.

Algorithm	Reduction of pesticide agent [%]	Grape as Grape **TT** [%]	Foliage as Grape **TF** [%]	Grape as Foliage **FT** [%]	Processing time [S]
Edge Based	30.59	90.4	9.59	73.48	0.65
Decision Tree	25.58	90.73	9.26	78.73	1.43
Moving Mask	26.79	90.7	9.67	79.18	1.15

Conclusions

Machine vision algorithms resulted in high detection rates of grape clusters, which can lead to significant reduction of chemical usage in vineyards. Spraying material use can be reduced by 30% while detecting and spraying 90% of the grape clusters. Reductions of 26% and 25% of material can be achieved when using GDA based on Moving Mask and Decision Tree, respectively. It is possible that a decision tree created from larger datasets will produce even better detection results. The parameters of the machine vision algorithms were optimized by analyzing the actual chemical reduction rates. They were tested on images taken at commercial vineyards while sampling a variety of grape species. This will ensure that the future robotic sprayer will not be limited to certain species. One important contribution of this work is the establishment of a publicly available dataset of photos taken at the vineyards. In order to implement these algorithms on an operational robotic sprayer, the algorithm processing time should not exceed 1.5 [S] for each image (assuming an average driving speed of 5 [km/h]). The machine vision algorithms are now ready to be used by the robotic sprayer and work in real-time conditions.

In the future we plan to integrate the machine vision system into our newly developed autonomous vineyard sprayer. We think combining the results from the three GDAs will result in even higher detection rates.

Acknowledgements

This research was partially supported by the Ministry of Science Slovenia-Israel Binational Fund, the Paul Ivanier Center for Robotics Research and Production Management, the Rabbi W. Gunther Plaut Chair in Manufacturing Engineering, Ben-Gurion University of the Negev, and the Pearlstone Center for Aeronautics Research.

References

[1] Pimentel, D. and H. Lehman, *The pesticide question: environment, economics, and ethics*. 1993: Kluwer Academic Pub.

[2] Tardiff, R.G., *Methods to assess adverse effects of pesticides on non-target organisms*. 1992: John Wiley & Son Ltd.

[3] Jeyaratnam, J., *Acute pesticide poisoning: a major global health problem.* World Health Statistics Quarterly, 1990. **43**(3): p. 139-144.

[4] Koh, D. and J. Jeyaratnam, *Pesticides hazards in developing countries.* Science of the Total Environment, The, 1996. **188**: p. 78-85.

[5] Ganzelmeier, H., *Innovative techniques and methods fort the saving of plant protection products.* Yearbook of Agriculture Engineering, 2004. **16**.

[6] Stentz, A., et al., *A system for semi-autonomous tractor operations.* Autonomous Robots, 2002. **13**(1): p. 87-104.

[7] Gillis, K.P., et al., *Injection and fluid handling system for machine-vision controlled spraying.* ASAE Paper, 2001: p. 01-1114.

[8] Balsari, P., G. Oggero, and M. Tamagnone, *Evaluation on different pesticide distribution techniques on apple orchards [Malus pumila Mill.-Piedmont]; Confronto fra differenti modalita'operative nella distribuzione di fitofarmaci al melo [Malus pumila Mill.-Piemonte].* Atti delle Giornate Fitopatologiche (Italy), 2000.

[9] Manor, G., Y. Gal, and H.R. Chicago. *Development of an accurate vineyard sprayer*. in *ASAE Annual International Meeting/ CIGR XVth World Congress*. 2002.

[10] Wiedemann, H.T., D.N. Ueckert, and W.A. McGinty, *Spray boom for sensing and selectively spraying small mesquite on highway rights-of-way.* Applied Engineering in Agriculture, 2002. **18**(6): p. 661-666.

[11] Zheng, J., *Intelligent pesticide spraying aims for tree target.* Resource, September. St. Joseph, MI: ASABE, 2005.

[12] Nishiwaki, K., K. Amaha, and R. Otani. *development of nozzle positioning system for precision sprayer*. in *Automation Technology for Off-Road Equipment*. 2004.

[13] Slaughter, D.C., D.K. Giles, and D. Downey, *Autonomous robotic weed control systems: A review.* Computers and Electronics in Agriculture, 2008. **61**(1): p. 63-78.

[14] Steward, B.L., L.F. Tian, and L. Tang, *Distance-based control system for machine vision-based selective spraying.* Transactions of the ASAE, 2002. **45**(5): p. 1255-1262.

[15] Shin, B.S., S.H. Kim, and J.U. Park, *Autonomous agricultural vehicle using overhead guide.* Automation Technology for Off-Road Equipment, Proceedings of the July, 2002: p. 26–27.

[16] Lamm, R.D., D.C. Slaughter, and D.K. Giles, *Precision weed control system for cotton.* Transactions of the ASAE, 2002. **45**(1): p. 231-238.

[17] Ogawa, Y., et al., *Spraying robot for grape production.* Spr Tra Adv Robot, 2006. **24**: p. 539-548.

[18] Lee, W.S., D.C. Slaughter, and D.K. Giles, *Robotic weed control system for tomatoes.* Precision Agriculture, 1999. **1**(1): p. 95-113.

[19] Shapiro, A., et al., *Toward elevated agrobotics: Development of a scaled-down prototype for visually guided date palm tree sprayer.* Journal of Field Robotics, 2009. **26**(6&dash): p. 572-590.

[20] Younse, P. and T. Burks, *Intersection Detection and Navigation for an Autonomous Greenhouse Sprayer using Machine Vision.* ME thesis. Gainesville, Fla.: University of Florida, Department of Agricultural and Biological Engineering, 2005.

[21] Jeon, H.Y., L.F. Tian, and T. Grift, *Development of an individual weed treatment system using a robotic arm.* American Society of Agricultural Engineers Paper Number, 2005. 51004.

[22] Canny, J., *A computational approach to edge detection.* IEEE Transactions on pattern analysis and machine intelligence, 1986: p. 679-698.

[23] Sharifi, M., M. Fathy, and M.T. Mahmoudi. *A classified and comparative study of edge detection algorithms*. 2002.

[24] Shin, M.C., D. Goldgof, and K.W. Bowyer. *An objective comparison methodology of edge detection algorithmsusing a structure from motion task*. in *Computer Vision and Pattern Recognition* 1998.

[25] Breiman, L., *Classification and regression trees*. 1984: Chapman & Hall/CRC.